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Projecting changes in regional temperature and precipitation extremes in the United States

Justin T. Schoof [a,*], Scott M. Robeson [b]

[a] Department of Geography and Environmental Resources, Southern Illinois University, Carbondale, IL 62901, USA
[b] Department of Geography, Indiana University, Bloomington, IN 47405, USA

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ABSTRACT

Regional and local climate extremes, and their impacts, result from the multifaceted interplay between large-scale climate forcing, local environmental factors (physiography), and societal vulnerability. In this paper, we review historical and projected changes in temperature and precipitation extremes in the United States, with a focus on strengths and weaknesses of (1) commonly used definitions for extremes such as thresholds and percentiles, (2) statistical approaches to quantifying changes in extremes, such as extreme value theory, and (3) methods for post-processing (downscaling) global climate models (GCMs) to investigate regional and local climate. We additionally derive regional and local estimates of changes in temperature extremes by applying a quantile mapping approach to high-resolution gridded daily temperature data for 6 U.S. sub-regions. Consistent with the background warming in the parent GCMs, we project decreases in regional and local cold extremes and increases in regional and local warm extremes throughout the domain, but the downscaling approach removes bias and produces substantial spatial variability within the relatively small sub-regions. We finish with recommendations for future research on regional climate extremes, suggesting that focus be placed on improving understanding of extremes in the context of large-scale circulation and evaluating the corresponding cascade of scale interactions within GCMs.

1. Introduction

Regional weather and climate extremes – unusual values of one or more variables for a specific geographic region and time of year – have substantial societal and economic impacts each year. Temperature extremes are closely linked to impacts on human health (Patz et al., 2005; O'Neill and Ebi, 2009; Mishra et al., 2015), short-term energy supply and demand (Schaeffer et al., 2012), transportation (Rowan et al., 2013), and many other sectors (Sivakumar, 2013). Precipitation extremes have widespread implications for agriculture (Anyamba et al., 2014) and transportation as well as flooding and urban drainage systems (Rosenberg et al., 2010). This paper aims to provide an overview of current issues associated with developing regional climate projections using global climate model (GCM) scenarios, with a focus on temperature and precipitation extremes in the United States.

Analyses that focus on changes in extremes within the observational record have identified widespread changes in the tails of the temperature distribution that are consistent with large-scale warming (Donat et al., 2013). Generally, changes in extremes associated with minimum temperature have been larger than those for maximum temperature, although recent warming (last 30 years) has been characterized by larger increases in warm anomalies relative to cold anomalies (Robeson et al., 2014). There have also been increases in precipitation extremes in many regions, but with less spatial homogeneity than temperature changes (Donat et al., 2013). Many land areas, including most regions within the United States, are characterized by positive trends in precipitation frequency and/or intensity (Alexander et al., 2006; Griffiths and Bradley, 2007; Groisman and Knight, 2007; Groisman et al., 2012; Donat et al. 2013; Guilbert et al., 2015). A growing body of evidence attributes large-scale changes in the frequency and/or intensity of temperature and precipitation extremes to radiative forcing from greenhouse gases (Christidis et al., 2011; Min et al., 2011; Zwiers et al., 2011) and highlights the need to quantify potential societal impacts from future changes.

In order to mitigate the impacts of changes in extremes, we must understand how such changes are manifested at the local to regional scale. This requires methods and approaches that are distinct from those used for the detection and attribution of extreme events. Model bias and the specific spatial scale of interest are critical considerations in this process. As an example, the

* Corresponding author.
E-mail address: jschoof@siu.edu (J.T. Schoof).

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comparison of point precipitation observations to output from GCMs has promoted the notion of the “drizzle problem”, whereby models show an altered probability distribution that has higher precipitation frequency and lower precipitation intensity. While not always interpreted in this way, the high frequency of precipitation in GCMs relative to station observations is not a model shortcoming, but instead the result of the difference in spatial scale (and also occurs in gridded observational precipitation; Ensor and Robeson, 2008). Contemporary GCMs, such as those used for the 5th Coupled Model Intercomparison Project (CMIP5; Taylor et al., 2012) are a key component of regional climate change projections, but their limited spatial resolution reduces their utility in estimating local or regional extremes without substantial post-processing (this is especially true in regions of large relief). Such post-processing typically includes bias correction as well as statistical or dynamical modeling, which is often referred to as downscaling.

The objective of this paper is to review the approaches used to project future climate extremes at the regional-to-local scale. While projections can be developed for a range of climatic variables, we focus on temperature and precipitation events at the daily timescale because of their climatic importance and clear societal impacts. The rest of the paper is organized as follows. Section 2 reviews existing metrics used to define temperature and precipitation extremes. Section 3 summarizes methods for developing high resolution projections of extremes given coarse output from contemporary GCMs. Section 4 describes results from previous studies engaged in projection of regional climate extremes for the US. In Section 5, examples of newly developed high resolution projections of regional temperature extremes are presented. The final section includes recommendations for future work.

2. Defining extremes

Given a climatic time series, extremes can be defined in many different ways. The simplest and most common approaches are based on threshold exceedances, such as the number of days for which the minimum temperature is below freezing. At a given location, approaches based on thresholds are easy to understand, but they make assessment of spatial patterns of changes in extremes difficult as they are not equally applicable in all climates (Wehner et al., 2013a) and can change relatively quickly with elevation or proximity to large water bodies. Percentile-based approaches, where the percentiles are defined in a spatially varying manner, such as the number of days exceeding the 95th percentile at a given location, are more amenable to exploring spatial variations in extremes. Several variations on threshold and percentile-based metrics were developed under the auspices of the World Meteorological Organization Commission for Climatology (CCl)/World Climate Research Programme (WCRP) project on Climate Variability and Predictability (CLIVAR) Expert Team on Climate Change Detection and Indices (ETCCDI) as described by Frich et al. (2002), Alexander et al. (2006) and Zhang et al. (2011). These are commonly referred to as the ETCCDI indicators and are summarized in Table 1.

The advantages of the ETCCDI indicators are that they are easy to interpret and are directly related to impacts in agriculture and other sectors. Furthermore, gridded ($2.5° \times 3.75°$) monthly and annual time series of the indicators have been made available as HadEX (Alexander et al., 2006) and HadEX2 (Donat et al., 2013). This makes them ideal for analysis of trends in extremes over large regions (e.g., Hartmann et al., 2013) and for comparison to extremes in output from GCMs (e.g., Collins et al., 2013). While some of the ETCCDI indicators are not indicative of truly extreme events (e.g., minimum temperatures below freezing are not extreme in most high latitude regions; Wehner et al., 2013a; Sato and Robeson, 2014), changes in their values represent changes in conditions that are likely to be accompanied by societal impacts. While the ETCCDI indicators include a few metrics aimed at changes in precipitation persistence, they are not well suited for characterizing changes in drought. They can therefore be supplemented by widely used drought indices, such as the Palmer Drought Severity

Table 1
List of indicators devised by the ETCCDI (see Section 2). T_{max} and T_{min} refer to daily maximum and minimum temperature, respectively. Shaded indicators are used in Section 5.

Indicator name	Abbrev.	Definition
Frost days	FD	Number of days with $T_{min} < 0$ °C
Icing days	ID	Number of days with $T_{max} < 0$ °C
Summer days	SU	Number of days with $T_{max} > 25$ °C
Tropical nights	TR	Number of days with $T_{min} > 20$ °C
Cool nights	TN10p	% of days with $T_{min} <$ the historical 10th percentile value
Warm nights	TN90p	% of days with $T_{min} >$ the historical 90th percentile value
Cool days	TX10p	% of days with $T_{max} <$ the historical 10th percentile value
Warm days	TX90p	% of days with $T_{max} >$ the historical 90th percentile value
Maximum T_{min}	TNx	Monthly maximum value of T_{min}
Minimum T_{min}	TNn	Monthly minimum value of T_{min}
Maximum T_{max}	TXx	Monthly maximum value of T_{max}
Minimum T_{max}	TXn	Monthly minimum value of T_{max}
Diurnal range	DTR	Monthly mean difference between daily T_{max} and T_{min}
Growing season length	GSL	Number of days between the first 6-day span with daily mean temperature above 5 °C and the first span after July 1 (in NH) with daily mean temperature below 5 °C
Warm spell duration index	WSDI	Annual count of at least six consecutive days with $T_{max} >$ the historical 90th percentile value
Cold spell duration index	CSDI	Annual count of at least six consecutive days with $T_{min} <$ the historical 10th percentile value
Maximum 1-day precipitation	RX1day	Monthly maximum 1-day precipitation (mm)
Maximum 5-day precipitation	RX5day	Monthly maximum consecutive 5-day precipitation amount (mm)
Simple daily intensity index	SDII	Mean precipitation amount on wet days (mm)
Number of heavy precipitation events	R10	Annual count of days with precipitation > 10 mm
Number of very have precipitation days	R20	Annual count of days with precipitation > 20 mm
Consecutive dry days	CDD	Maximum number of consecutive days with precipitation < 1 mm
Consecutive wet days	CWD	Maximum number of consecutive days with precipitation > 1 mm
Very wet days	R95p	Annual total precipitation derived from days > 95th percentile
Extremely wet days	R99p	Annual total precipitation derived from days > 99th percentile
Annual total precipitation	PRCPTOT	Annual total precipitation on all days.